# Is trading volume still a determinant of cross-autocorrelations in stock returns?

Kasper Ruohonen

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Finance Department, Aalto University School of Business

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**Abstract**

I used daily CRSP data of stocks traded at NYSE and AMEX exchanges from 1963 to 2019 to investigate whether the returns of portfolios constructed of stocks with high trading volume lead the returns of portfolios constructed of stocks with low trading volume. Turnover acts as a stand-in for trading volume to disentangle size effect from the cross-autocorrelations, making the independent effect of trading volume more visible. Results provide significant evidence of high volume portfolio returns leading the returns of low volume portfolios, although the effect has diminished over time, compared to previous studies and samples.

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## 1. Introduction & Research problem

This paper examines the relevancy of a discovery made by Tarun Chordia and Bhaskaran Swaminathan (2000), where they proved that trading volume is a determinant of lead-lag patterns found in stock returns. Their study was motivated by the findings of Lo and MacKinlay (1990), who found that lagged returns of large firms were more correlated with current returns of small firms, than lagged returns of small firms were with current returns of large firms.

There has been many explanation propositions for these patterns, from which Chordia and Swaminathan (2000), as well as this paper, tested the speed of adjustment hypothesis, which suggests that some stocks react faster to common market information than others.

The main hypothesis of this paper is that stocks with higher trading volume lead the returns of stocks with lower trading volume, or in other words: trading volume is a determinant of cross-autocorrelation patterns in stock returns. Since this thesis is an attempt to study whether Chordias and Swaminathans (2000) findings hold value today, the hypothesis used is the same that they had in their paper. Their results will also be used as a benchmark for this paper. Their paper called "Trading Volume and Cross-Autocorrelations in Stock Returns", will be referenced multiple times in this thesis, and from this point forward might be referred to as the "original study", or just by their names along side of the traditional referencing to keep the flow in the core text.

My main sample consists of NYSE and AMEX stocks from 1963 to 2019. I also did a replication of the original sample by Swaminathan and Chordia (2000), which included stocks from 1963 to 1996.

Based on vector autoregressions and Dimson beta regressions, the results are a bit mixed, but they mostly support the hypothesis. The individual lead-lag effect of volume, measured by turnover, can be seen using both regressions with significant values. The theory has lost a lot of effectiveness over time, judging by the estimates of the regressions and simple cross-autocorrelations. Although not intentional, the regressions also indicate that size still has an individual effect on these patterns as well. This accidental observation combined with other recent research on the matter suggests that size might be the main factor behind the lead-lag patterns.

My thesis mostly uses the exact same methods as Swaminathan and Chordia. I do make a few exceptions from the original study. But like mentioned, I will be replicating and reporting their sample (years 1963 – 1996), along with the main sample, to show what the results would have been with my methods, and to point out that the data they used has also changed a little bit overtime, probably for the better. This also paints an overview of how the theory has changed since the first discovery and gives me an opportunity to discuss those changes. The exceptions I made from the methods of the original study will be explained as they come.

## 2. Literature review

Finance literature is filled with theories and studies that have found a way to predict future stock returns. Cross-autocorrelations are one highly used tool to find qualities that hold predictive powers. Most of the more important studies involving cross-autocorrelations were conducted between 1990 and 2000, however there is constant interest on this field, but alike with any other more specific field, the research questions have become more and more narrow and focused. My paper revolves around the broader view of cross-autocorrelations and the literature review will not be an exception.

Like mentioned at the start of introduction, the niche that this thesis bases itself on, was started by Lo and MacKinlay (1990), who found positive portfolio cross-autocorrelations stemming from individual securities. Further they found that larger firms where the leading group in identifying these cross-autocorrelations. They argued that this is due to larger stocks adjusting faster to new common market information. McQueen, Pinegar & Thorley (1996) expanded Lo & McKinlays work and noticed that firms with small capitalization responded sluggishly to good news, but not to bad news.

Some studies argued nonsynchronous-trading to be the main reason behind portfolio cross-autocorrelations because it creates autocorrelation in low volume stocks, which is more usual in small capitalization firms. Richardson & Peterson (1999) found evidence indicating that even after controlling for autocorrelations in small cap firms, the cross-autocorrelations still exist between small and large firms.

Hameed (1997) was one of the first who linked trading volume more firmly to cross-autocorrelations. Brennan, Jegadeesh and Swaminathan (1993) examined and found that firms that are being followed by many analysts lead the returns of firms that aren't being followed by as many analysts, this is well connected to the paper, discussed in the introduction and will be discussed many more times in this thesis, by Swaminathan and Chordia (2000) who then studied whether trading volume could hold value, independent from firm size, as a determinant of cross-autocorrelations and found significant results that it does. They used the methods and findings of Brennan, Jegadeesh and Swaminathan (1993) to link portfolio cross-autocorrelations to individual securities.

Similar studies to Swaminathan and Chordia (2000) & Lo and McKinlay (1990) have since been conducted in different environments and markets. The same effects (large cap firms leading small cap firms, high volume firms leading low volume firms) seem to persist in different markets around the world. These, let's call them, "horizontal replications" (similar time period, different place) include at least, but not limited to, Asia (Chang, McQueen & Pinegar, 1999), German & Turkey (Altay, 2003), New Zealand (Choi & Zao, 2007), London (Mills & Jordanov, 2001), Warsaw (Gebka, 2008), Stockholm (Säfvenblad, 2000) and Athens (Drakos, 2016). These studies all have their own characteristics, but the central point of them remains the same, the lead-lag patterns have been an established characteristic in both emerging and already developed markets.

Most popular reasoning for the existence for trading volume and size lead-lag effects is traditional market barriers like trading costs, lack of information and stock priorities within institutions. Mech (1993) proved transaction costs to cause stocks to have delayed adjustments to information. Swaminathan and Chordia (2004) found evidence that information asymmetry within subsets of stocks and cross-trading costs could be the birthplace of the cross-autocorrelations. More recently Hameed, Lof & Suominen (2018) provide evidence that the cross-autocorrelations are due to institutions placing lower trading priority in small illiquid stocks.

Most of the research in this field, including the flagships of Lo & McKinlay (1993) and Swaminathan & Chordia (2000), has been conducted observing US markets, usually using NYSE and AMEX stock data, which I will also be using. My focus turns back to the origins of the research and examining whether these cross-autocorrelations still exist.

# 3. Data & methods & results

## 3.1 Sample summary

The main sample data consists of all ordinary common shares traded at NYSE or AMEX from 1963 to 2019. Data is provided by CRSP. Years starting from 1963 to 1996 are also used for the replication sample discussed above.

The sample is divided into 16 equal-weighted portfolios each year based on the size of the firms and turnover ratios of their stocks. First, the firms are divided into four quartiles based on the total market value of equity on the last trading day of the previous year. Then the four size quartiles are further divided into four groups each, based on their average daily turnover in the previous year.

Because the lead-lag patterns were first identified using firm size as a metric, controlling for firm size is crucial for examining the independent impact of trading volume. Turnover is used in this study as a measure of trading volume because it extracts the effect of firm size from raw trading volume. Furthermore, the portfolios are divided into size groups for the same reasoning. Turnover and volume as terms are used interchangeably in this thesis.

To tackle non-trading issues, a stock had to have at least 90 observations of daily trading volume to be included in the final portfolios. This especially affects the smallest size and lowest average turnover portfolio or portfolios.

Daily and weekly portfolio returns are computed by averaging the non-missing returns of the stocks in the portfolio. Daily CRSP data is used to calculate both the daily and the weekly portfolio returns. In addition to omitting stocks that did not trade at date *t*, stocks that did not trade at date *t-1* are omitted from the portfolio returns as well, to further reduce the effects of nonsynchronous trading in the results.

To mitigate seasonal patterns in weekly returns, weekly returns are measured from Wednesday close to the following Wednesday close. Seasonal patterns in weekly returns is a problem studied by Bessembinder and Hertzel (1993), which suggests that weekly return autocorrelations and correlations are abnormal if the week breaking point is near the weekend.

Table 1.

Summary statistics for the main sample: years 1963 to 2019. In P(i,j) i refers to the portfolios size quartile and j to the turnover quartile. i (j) = 1 represents the smallest (lowest) and 4 the largest (highest) size (turnover). EW is an equal-weighted market portfolio of all the firms in the sample. $p_k$ refers to the *k*th order autocorrelation and $S_k$ to the sum of *k* first autocorrelations. N represents the average number of firms in $P_{i,j}$ each day or each week. The size and turnover numbers refer to the average firm in those portfolios, they are computed by averaging yearly medians and means. Size figures are in billions of dollars.

Panel A: 1963-2019

| | Statistics for daily returns | | | | | Statistics for weekly returns | | | | | Size | | Turnover | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| PF | Mean (%) | St.Dev (%) | $p_1$ | $S_{10}$ | N | Mean (%) | St.Dev (%) | Wed. $p_1$ | Wed. $S_4$ | N | Med | Mean | Med (%) | Mean (%) |
| P11 | 0.26 | 1.04 | 0.16 | 1.08 | 71 | 0.47 | 2.19 | 0.33 | 0.81 | 112 | 0.026 | 0.037 | 0.052 | 0.146 |
| P12 | 0.19 | 1.01 | 0.23 | 1.03 | 93 | 0.43 | 2.46 | 0.30 | 0.72 | 120 | 0.065 | 0.046 | 0.097 | 0.206 |
| P13 | 0.15 | 1.12 | 0.20 | 0.84 | 102 | 0.36 | 2.80 | 0.27 | 0.59 | 120 | 0.047 | 0.056 | 0.157 | 0.308 |
| P14 | 0.11 | 1.36 | 0.22 | 0.78 | 108 | 0.25 | 3.62 | 0.22 | 0.46 | 118 | 0.049 | 0.062 | 0.302 | 0.681 |
| P21 | 0.09 | 0.94 | 0.05 | 0.32 | 103 | 0.29 | 2.05 | 0.11 | 0.27 | 122 | 0.249 | 0.281 | 0.104 | 0.162 |
| P22 | 0.07 | 1.10 | 0.07 | 0.32 | 118 | 0.30 | 2.56 | 0.13 | 0.29 | 124 | 0.280 | 0.305 | 0.204 | 0.298 |
| P23 | 0.07 | 1.22 | 0.11 | 0.35 | 120 | 0.27 | 2.92 | 0.12 | 0.26 | 124 | 0.299 | 0.322 | 0.311 | 0.450 |
| P24 | 0.05 | 1.47 | 0.13 | 0.32 | 121 | 0.20 | 3.54 | 0.11 | 0.23 | 123 | 0.311 | 0.345 | 0.565 | 0.843 |
| P31 | 0.07 | 0.83 | 0.07 | 0.23 | 118 | 0.29 | 2.89 | 0.10 | 0.19 | 124 | 0.991 | 1.086 | 0.158 | 0.210 |
| P32 | 0.06 | 0.94 | 0.11 | 0.26 | 123 | 0.29 | 2.21 | 0.11 | 0.19 | 126 | 1.051 | 1.130 | 0.267 | 0.357 |
| P33 | 0.06 | 1.13 | 0.14 | 0.26 | 123 | 0.27 | 2.70 | 0.10 | 0.17 | 124 | 1.049 | 1.135 | 0.392 | 0.518 |
| P34 | 0.05 | 1.40 | 0.13 | 0.21 | 121 | 0.21 | 3.31 | 0.08 | 0.13 | 123 | 1.002 | 1.112 | 0.660 | 0.929 |
| P41 | 0.05 | 0.82 | 0.07 | 0.06 | 125 | 0.23 | 1.80 | 0.04 | 0.06 | 127 | 9.849 | 21.903 | 0.185 | 0.221 |
| P42 | 0.05 | 0.91 | 0.08 | 0.04 | 126 | 0.24 | 2.01 | 0.03 | 0.06 | 127 | 6.447 | 10.520 | 0.273 | 0.333 |
| P43 | 0.05 | 1.02 | 0.10 | 0.06 | 125 | 0.25 | 2.32 | 0.02 | 0.04 | 126 | 4.702 | 7.663 | 0.365 | 0.449 |
| P44 | 0.05 | 1.31 | 0.10 | 0.08 | 124 | 0.22 | 2.99 | 0.03 | 0.05 | 124 | 3.811 | 5.740 | 0.583 | 0.766 |
| EW | 0.08 | 0.99 | 0.15 | 0.41 | | 0.29 | 2.38 | 0.15 | 0.31 | | | | | |

Panel B: replication sample 1963-1997

| | Statistics for daily returns | | | | | Statistics for weekly returns | | | | | Size | | Turnover | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| PF | Mean (%) | St.Dev (%) | $p_1$ | $S_{10}$ | N | Mean (%) | St.Dev (%) | Wed. $p_1$ | Wed. $S_4$ | N | Med | Mean | Med (%) | Mean (%) |
| P11 | 0.32 | 1.09 | 0.20 | 1.28 | 68 | 0.54 | 2.34 | 0.38 | 0.91 | 118 | 0.013 | 0.013 | 0.044 | 0.075 |
| P12 | 0.24 | 1.03 | 0.26 | 1.24 | 93 | 0.51 | 2.51 | 0.37 | 0.89 | 129 | 0.013 | 0.013 | 0.072 | 0.121 |
| P13 | 0.19 | 1.06 | 0.27 | 1.08 | 104 | 0.41 | 2.69 | 0.35 | 0.77 | 129 | 0.014 | 0.015 | 0.102 | 0.182 |
| P14 | 0.13 | 1.15 | 0.31 | 1.01 | 114 | 0.29 | 3.10 | 0.30 | 0.66 | 129 | 0.015 | 0.016 | 0.159 | 0.286 |
| P21 | 0.11 | 0.65 | 0.37 | 1.29 | 103 | 0.33 | 1.72 | 0.33 | 0.69 | 131 | 0.061 | 0.065 | 0.041 | 0.072 |
| P22 | 0.09 | 0.80 | 0.34 | 0.97 | 123 | 0.33 | 2.25 | 0.27 | 0.55 | 132 | 0.061 | 0.067 | 0.079 | 0.141 |
| P23 | 0.07 | 0.97 | 0.31 | 0.81 | 127 | 0.28 | 2.64 | 0.24 | 0.47 | 132 | 0.062 | 0.068 | 0.126 | 0.218 |
| P24 | 0.06 | 1.19 | 0.26 | 0.60 | 129 | 0.20 | 3.12 | 0.22 | 0.41 | 131 | 0.063 | 0.071 | 0.217 | 0.372 |
| P31 | 0.07 | 0.56 | 0.37 | 1.04 | 122 | 0.31 | 1.60 | 0.28 | 0.50 | 132 | 0.244 | 0.267 | 0.042 | 0.072 |
| P32 | 0.07 | 0.71 | 0.35 | 0.81 | 131 | 0.31 | 2.00 | 0.23 | 0.39 | 135 | 0.258 | 0.281 | 0.084 | 0.143 |
| P33 | 0.06 | 0.91 | 0.32 | 0.63 | 131 | 0.29 | 2.49 | 0.19 | 0.34 | 133 | 0.248 | 0.278 | 0.139 | 0.225 |
| P34 | 0.05 | 1.21 | 0.22 | 0.41 | 129 | 0.22 | 3.09 | 0.16 | 0.27 | 131 | 0.248 | 0.281 | 0.251 | 0.403 |
| P41 | 0.05 | 0.66 | 0.25 | 0.36 | 133 | 0.24 | 1.68 | 0.13 | 0.19 | 135 | 1.396 | 3.756 | 0.064 | 0.088 |
| P42 | 0.05 | 0.73 | 0.25 | 0.28 | 135 | 0.25 | 1.87 | 0.10 | 0.14 | 136 | 1.477 | 2.723 | 0.104 | 0.141 |
| P43 | 0.06 | 0.83 | 0.25 | 0.27 | 134 | 0.27 | 2.13 | 0.09 | 0.13 | 135 | 1.400 | 2.330 | 0.141 | 0.190 |
| P44 | 0.05 | 1.10 | 0.19 | 0.25 | 132 | 0.23 | 2.76 | 0.10 | 0.15 | 133 | 1.158 | 1.727 | 0.232 | 0.336 |
| EW | 0.09 | 0.81 | 0.34 | 0.85 | | 0.32 | 2.21 | 0.26 | 0.51 | | | | | |

Table 1 represents the summary statistics of the sample from 1963 to 2019 in panel A and the replication sample from 1963 to 1996 in Panel B. Discussion in this section is centered around the main sample. The core text is supposed to revolve around the main sample, so if not specifically mentioned, I am not talking about the replicate.

Like I mentioned before the table, omitting stocks that did not trade at date *t* or *t-1* affects the smallest and lowest turnover portfolios the most, especially on a daily level. On a daily level, the smallest size quartile, lowest turnover portfolio ($P_{11}$) has only 71 firms contributing to the returns on average. $P_{12}$, $P_{13}$, $P_{14}$ and $P_{21}$ are also affected by this procedure (93, 102, 108, 103) comparing to the rest of the portfolios, which have 118-126 firms on average each. On a weekly level only $P_{11}$ seems to have taken a clear hit, although the missing daily returns cause the weekly returns to be upward bias, even though it can't be seen straight from the average number of firms contributing. The returns on both the replica and the main sample are noticeably upward bias in the smaller portfolios because of this, but that bias disappears in the larger portfolios. Good to note that the values of the returns alone are not what is important in this paper.

Sizes of the firms in a portfolio grow with the turnover, except in the biggest quartile, where the biggest turnover interestingly has by far the smallest firms (mean size highest turnover = 5.740 and lowest = 21.903). This truly offers a chance to see whether trading volume holds independent value in determining lead-lag patterns. Also the differences in sizes of the firms in the third quartiles lowest (mean = 1.086) and highest (1.112) turnover portfolios is also very small, ideal for my purposes. Comparing the two samples to each other shows, like expected, quite large growth in sizes of the firms overall.

The autocorrelations decrease when moving from smaller sized quartiles to larger. Especially after the first lag, the autocorrelations of the firms in the largest quartile are almost non-existent. Daily autocorrelations are larger than weeklies, which again, is expected, since a week is a lot more time for a portfolio to adjust to new information than a day, so the larger inspection interval absorbs some of the autocorrelation. Surprisingly, the first order daily autocorrelations, and to some extent the sum of the first ten, go up with the turnover in the largest size quartile (quartile 4).

Intuitively, if I have a stock or a portfolio that adjusts slowly to new information, their autocorrelations should be larger than those of a stock or a portfolio that adjusts faster to new information, since price increases would follow price increases and decreases would follow decreases. In reality, like Chordia & Swaminathan (2000) point out, individual stocks rarely experience noticeable positive autocorrelation, but it does hold in the case of portfolios, according to Lo and MacKinlay (1990). So the autocorrelations going into the same direction as the turnover in the one quartile that has the smallest firms in the highest turnover portfolio, is actually against the hypothesis.

A portion of the autocorrelations in the smaller portfolios can be pinned down to non-trading. But, like Chordia and Swaminathan (2000), again, point out in their paper, another study by Boudoukh, J., Richardson, MP. & Whitelaw, RE. (1994) shows that the autocorrelations would still very much exist even when non-trading is taken into account.

The summaries of both samples already show that the autocorrelations of individual stocks have decreased over time, which is expected. Effects found in financial studies have a tendency to diminish after the publication (Mclean & Pontiff, 2016), this is a reoccurring theme in this thesis. And even though the simple autocorrelations in some portfolios are relatively small, that itself is not a problem since I am more interested in the cross-autocorrelations of these portfolios.

Comparing my replication sample against the work of Swaminathan and Chordia (2000) on a broader sense shows minor differences in almost every column, this is mostly due to CRSP data changing over time. I do some things differently in the empirical testing that follows and I will mention those differences along the way. I do want to highlight, that the point of this thesis is to see whether the hypothesis in Chordias and Swaminathans (2000) work still holds up. The point is not to see how well I can replicate their study. From this point onwards the reports of the replication results can be found in the appendix at the end of the thesis, but I do mention and discuss them briefly at some parts of the core text.

### 3.2 Cross-autocorrelations

Cross-autocorrelations are reported in table 3 (replicate in the appendix 1). Only the lowest and highest turnover portfolios of each size quartile are included.

Table 2.

$r_{ij,\,t}$ stands for portfolio returns at date t, in the size quartile i and turnover quartile j.

| Daily returns | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| $r_{ij,\,t}$ | $r_{11,\,t}$ | $r_{14,\,t}$ | $r_{21,\,t}$ | $r_{24,\,t}$ | $r_{31,\,t}$ | $r_{34,\,t}$ | $r_{41,\,t}$ | $r_{44,\,t}$ |
| $r_{11,\,t-1}$ | 0.16 | 0.18 | 0.11 | 0.09 | 0.10 | 0.06 | 0.05 | 0.03 |
| $r_{14,\,t-1}$ | 0.27 | 0.22 | 0.11 | 0.11 | 0.10 | 0.07 | 0.05 | 0.04 |
| $r_{21,\,t-1}$ | 0.20 | 0.16 | 0.05 | 0.07 | 0.06 | 0.05 | 0.03 | 0.03 |
| $r_{24,\,t-1}$ | 0.25 | 0.24 | 0.12 | 0.13 | 0.12 | 0.10 | 0.07 | 0.07 |
| $r_{31,\,t-1}$ | 0.20 | 0.16 | 0.06 | 0.08 | 0.07 | 0.06 | 0.04 | 0.04 |
| $r_{34,\,t-1}$ | 0.25 | 0.24 | 0.13 | 0.15 | 0.14 | 0.13 | 0.09 | 0.09 |
| $r_{41,\,t-1}$ | 0.19 | 0.16 | 0.08 | 0.10 | 0.11 | 0.09 | 0.07 | 0.06 |
| $r_{44,\,t-1}$ | 0.23 | 0.23 | 0.12 | 0.15 | 0.14 | 0.13 | 0.09 | 0.10 |

| Weekly returns | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| $PF_{ij,t}$ | $r_{11,\,t}$ | $r_{14,\,t}$ | $r_{21,\,t}$ | $r_{24,\,t}$ | $r_{31,\,t}$ | $r_{34,\,t}$ | $r_{41,\,t}$ | $r_{44,\,t}$ |
| $r_{11,\,t-1}$ | 0.33 | 0.20 | 0.14 | 0.09 | 0.09 | 0.05 | 0.01 | 0.01 |
| $r_{14,\,t-1}$ | 0.33 | 0.22 | 0.12 | 0.09 | 0.07 | 0.04 | -0.01 | 0.00 |
| $r_{21,\,t-1}$ | 0.30 | 0.20 | 0.11 | 0.08 | 0.07 | 0.04 | 0 | 0 |
| $r_{24,\,t-1}$ | 0.33 | 0.24 | 0.15 | 0.11 | 0.10 | 0.07 | 0.02 | 0.02 |
| $r_{31,\,t-1}$ | 0.30 | 0.21 | 0.14 | 0.10 | 0.10 | 0.06 | 0.02 | 0.02 |
| $r_{34,\,t-1}$ | 0.32 | 0.24 | 0.17 | 0.13 | 0.13 | 0.08 | 0.04 | 0.04 |
| $r_{41,\,t-1}$ | 0.25 | 0.18 | 0.15 | 0.10 | 0.13 | 0.07 | 0.04 | 0.04 |
| $r_{44,\,t-1}$ | 0.30 | 0.23 | 0.15 | 0.12 | 0.13 | 0.08 | 0.04 | 0.03 |

In cross-autocorrelations the interest is in comparing two portfolios inside the same size quartile to each other, their own autocorrelations and their cross-autocorrelations. Similarly to the autocorrelations of individual portfolios, the cross-autocorrelations go down while size increases. On a daily level the differences in the cross-autocorrelations, although small, are still very much present even in the largest quartile. But on a weekly level, both the cross-autocorrelations and the differences in them become so small that strong conclusions cannot be drawn, solely based on them.

Besides smallest (0,33 & 0,33) and largest quartile (0,04 & 0,04) of the weekly returns, low volume portfolios correlate more with the lagged returns of high volume portfolios ($r_{i1,\,t}$ & $r_{i4,\,t-1}$), than their own lagged values ($r_{i1,\,t}$ & $r_{i1,\,t-1}$), and even in those two, the correlations are equal. This is an indication that the lagged high volume portfolio returns would contain more predictive powers in relation to the low volume portfolios, than low volume portfolios in relation to themselves.

In all the cross-autocorrelations, except the largest size quartile weekly returns (0,04 & 0,04) the correlations are bigger using the lagged returns of the high volume portfolio ($r_{i,4,\,t-1}$) and current low volume portfolio returns ($r_{i,1,\,t}$) than using lagged returns of the low volume portfolio ($r_{i,1,\,t-1}$) and current returns of the high volume portfolio ($r_{i,4,\,t}$). Indicating that high volume portfolio returns would be more useful at predicting low volume portfolio returns than low volume portfolio returns are at predicting high volume portfolio returns.

Briefly comparing these results to the replicate sample, the samples differ in cross-autocorrelations the same way they differ in the summary statistics. The correlations as well as the differences in correlations have gone down with time in every size quartile. This would be evidence that the predictive powers of trading volume have lost some of it's merit.

### 3.3 Vector Autoregressions

Like Chordia and Swaminathan (2000), I'm conducting two type of regressions to test the hypothesis. Vector autoregressions (VAR from this point forward), which will be covered in this section and Dimson beta regressions in the next section. Questions that I am interested with the VARs remain the same as they were with Chordia & Swaminathan (2000): (1) Do cross-autocorrelations have information independent from own autocorrelations? (2) Is the ability of returns on high volume stocks to predict returns on low volume stocks better than the ability of returns on low volume stocks to predict returns on high volume stocks?

To test what effects high volume portfolio returns and low volume portfolio returns have in each other, I test (as well as the original study) the following bivariate vector autoregression:

$$r_{i1,t} = a_0 + \sum_{k=1}^{K} a_k r_{i1,\ t-k} + \sum_{k=1}^{K} b_k r_{i4,\ t-k} + u_t$$

$$r_{i4,t} = c_0 + \sum_{k=1}^{K} c_k r_{i1,\ t-k} + \sum_{k=1}^{K} d_k r_{i4,\ t-k} + v_t$$

VAR regressions are conducted using only the lowest and the highest turnover portfolios inside the size quartiles. To answer question (1) I check whether the coefficients contributing to $\sum_{k=1}^{K} b_k r_{i4,\ t-k}$ are greater than 0, in other words whether the sum of the coefficients derived from the lagged returns of the high volume portfolio is greater than 0. The daily VAR regressions are run with five lags (k = 5) and weekly VAR regressions are run with one lag (k = 1).

To answer the more important (2) question I need to test whether $\sum_{k=1}^{K} b_k r_{i4,\ t-k}$ is larger than $\sum_{k=1}^{K} c_k r_{i1,\ t-k}$. Or to be more clear whether high volume portfolio return estimates predicting low volume portfolio returns are greater, than low volume portfolio return estimates predicting high volume portfolio returns. Formally the null-hypothesis: $\sum_{k=1}^{K} b_k r_{i4,\ t-k} = \sum_{k=1}^{K} c_k r_{i1,\ t-k}$ and the alternative hypothesis $\sum_{k=1}^{K} b_k r_{i4,\ t-k} > \sum_{k=1}^{K} c_k r_{i1,\ t-k}$ (i.e the test is one-sided).

Because of the regression coefficients about to be shown, in addition to the autocorrelations and cross-autocorrelations decreasing over time, I'm testing whether $\sum_{k=1}^{K} b_k r_{i4,\ t-k} > \sum_{k=1}^{K} c_k r_{i1,\ t-k}$ with one lag on both, daily and weekly returns to avoid noise. Also the weekly regressions already capture longer term effects. This differs from the original study, where daily returns were tested with all 5 lags.

Daily and weekly VAR regression estimates are shown in table 3.

### *3.3.1 Daily return results*

On a daily level, most of the estimates are significant on a 1 percent level. H1 is significant at the 1 percent level in every portfolio. It also appears that the lagged high turnover portfolio returns have a better ability to predict current low turnover portfolio returns, than the lagged low portfolio returns have to predict current low portfolio returns (the H1 & high are larger than L1 & low in the $P_{i1}$ rows).

Table 4.

LHS = Left hand side of the equation, L1 refers to the first lag of the low volume portfolio in the same size quartile (= $a_k r_{i1,\ t-1}$ or $c_k r_{i1,\ t-1}$). Low refers to the sum of the low volume portfolio coefficients ($\sum_{k=1}^{K} a_k r_{i1,\ t-k}$ or $\sum_{k=1}^{K} c_k r_{i1,\ t-k}$). H1 refers to the first lag of the high volume portfolio in the same size quartile ($b_k r_{i4,\ t-1}$ or $d_k r_{i4,\ t-k}$). High refers to the sum of the high volume portfolio coefficients ($\sum_{k=1}^{K} b_k r_{i4,\ t-k}$ or $\sum_{k=1}^{K} d_k r_{i4,\ t-k}$). $R^2$ refers to the adjusted coefficient of determination. Z(A) refers to the z-test of whether $\sum_{k=1}^{K} b_k r_{i4,\ t-k} = \sum_{k=1}^{K} c_k r_{i1,\ t-k}$, with the alternative hypothesis of $\sum_{k=1}^{K} b_k r_{i4,\ t-k} > \sum_{k=1}^{K} c_k r_{i1,\ t-k}$. All statistics are rpdouced using white heteroscedasticity correction. ***, **, * refer to significance at 1, 5 and 10 percent levels, respectively.

| Panel A: Daily returns | | | | | | |
|---|---|---|---|---|---|---|
| LHS | L1 | Low | H1 | High | $\bar{R}^2$ | Z(A) |
| P11 | -0.0265* | 0.1845*** | 0.1849*** | 0.2698*** | 0.10 | 3.75*** |
| P14 | 0.0794*** | 0.1956*** | 0.1630*** | 0.2629*** | 0.07 | |
| P21 | -0.1777*** | -0.1849*** | 0.1644*** | 0.2414** | 0.03 | 6.66*** |
| P24 | -0.2267*** | -0.3150*** | 0.2468*** | 0.3697*** | 0.03 | |
| P31 | -0.1903*** | -0.2980*** | 0.1761*** | 0.2891*** | 0.04 | 7.68*** |
| P34 | -0.2779*** | -0.5000*** | 0.2633*** | 0.4231*** | 0.03 | |
| P41 | -0.0334 | -0.0509 | 0.0756*** | 0.0722* | 0.01 | 3.30*** |
| P44 | -0.1464*** | -0.2109*** | 0.1786*** | 0.1873** | 0.02 | |

| Panel B: Weekly returns | | | | | | |
|---|---|---|---|---|---|---|
| P11 | 0.1861*** | | 0.117*** | | 0.13 | -0.32 |
| P14 | 0.1444** | | 0.1517*** | | 0.05 | |
| P21 | -0.0770 | | 0.1243*** | | 0.02 | 2.01** |
| P24 | -0.1271 | | 0.1780*** | | 0.01 | |
| P31 | -0.0647 | | 0.1088*** | | 0.02 | 1.71** |
| P34 | -0.1038 | | 0.1361** | | 0.01 | |
| P41 | 0.0354 | | 0.0042 | | 0.002 | -0.19 |
| P44 | -0.0169 | | 0.0398 | | 0.001 | |

$\bar{R}^2$ can be interpreted as predictability of the LHS with the right hand side equation. So there's additional interest in $\bar{R}^2$, because it allows comparisons, whether low or high turnover portfolio returns are more predictable. $\bar{R}^2$ reveals that the predictability of returns in the smallest size quartile is higher on the low turnover portfolios than the high turnover portfolios. But in the second size quartile they're equal and in the third and fourth the difference is 0.01, with low turnover portfolio returns being more predictable in the third quartile and high turnover portfolio returns in the fourth quartile. Overall, the $\bar{R}^2$ values are quite low, so the answer to whether low or high turnover portfolio returns are more predictable is inconclusive.

The most interesting value out of these coefficients is the P41 H1 and High results. In every other low turnover portfolio ($P_{i1}$) the sum of the lagged high turnover portfolio return estimates is clearly larger than the H1 results and remains significant at the 1 percent level with all the 5 lags (not individually, but together), even though the effect of the $P_{i4}$ lagged returns deteriorates after the first one. In P41, the sum of the 5 lags is slightly smaller than the first lag alone. Now this is partly the reason, I only conduct the daily Z-tests with one lag, similarly to the weekly regressions.

Daily Z-tests are all significant at the 1 percent level, stating that at least very short term, high volume portfolios are better at predicting low volume portfolio returns than vice versa.

Comparing this to the replicate (appendix 2), the H1 values in $P_{i1}$ have decreased over time, but the Z-test results remain significant and depending on the size quartile are even more convincing than the ones with 1963-1996 sample.

### 3.3.2 *Weekly return results*

Weekly returns are not quite as convincing, but the H1 estimates in the low turnover portfolios, which are the most important figures in these regressions, are significant at the 1 percent level, with the exception of P41. L1 values are only significant in P11 and P14, P11 at 1 percent level and P14 at 5 percent level.

The estimates show that with weekly returns, the ability of $P_{i4,\,t-1}$ returns to predict $P_{i1,\,t}$ returns is not better, than $P_{i1,\,t-1}$ returns to predict $P_{i1,\,t}$ returns, in the size quartiles one and four. This is not surprising in the largest size, although the quartile 1 coefficients do come as a surprise. In these two quartiles the L1 value is actually bigger than the H1. In P11 the H1 coefficient (0.117) is significant, but the L1 is even bigger. In P41 both values (L1 & H1) are insignificant.

These results fit well into the pattern of this study so far, where the very short-term cross-autocorrelations effects remain, but longer, in this case weekly return cross-autocorrelations are becoming harder to observe, and seem to have faded away at least a little bit.

In weekly returns the low turnover portfolio $\bar{R}^2$:s are approximately double of high turnover $\bar{R}^2$, indicating that the predictability is much better in the $P_{i1}$ portfolios. However the $\bar{R}^2$ values turn very poor in the bigger size quartiles, to the point that I had to make an exception and report more than two decimals, so that I wouldn't have to report a zero.

The weekly return Z-tests indicate significancy at the 5% level in the two central size quartiles, but the smallest and the largest are no way near being significant. Like said earlier, significant results in the largest quartile would be the strongest evidence in favor of the hypothesis, because in that quartile sizes of the firms in the portfolios go down when turnover grows. Significant results in size quartile 3 is also important, which I do get with the VAR-regressions.

### 3.4 Dimson Beta Regressions

In the VAR tests I tested the lead-lag effects inside each size quartile, comparing low and high volume portfolios to each other. Now with Dimson beta regressions, I am still measuring similar effects, but in a different form. With Dimson beta regressions, I test every size quartile against one common benchmark.

Dimson beta regression is very similar to the basic beta regression, but in addition to the contemporaneous beta, market portfolio leads and lags are taken in to account as independent variables. (Dimson, 1979)

The left hand side of the equations are constructed by deducting the low turnover portfolio returns from the high turnover portfolio returns inside the size quartile, essentially forming a zero net investment portfolio that is long in the high turnover portfolio ($P_{i4}$) and short in the low turnover portfolio ($P_{i1}$). Equal-weighted market portfolio formed from NYSE and AMEX firms (bottom row of the summary statistics) is acting as the market portfolio in these regressions. The equation looks like this:

$$r_{O,t} = a_O + \sum_{k=-K}^{K} \beta_{O,k}\, r_{m,\ t-k} + u_{O,t}$$

Where $\beta_{O,k} = \beta_{i4,k} - \beta_{i1,k}$.

Because Beta is a value that measures portfolios or stocks exposure to market fluctuation, intuitively if the high turnover portfolio responds faster to new market information its beta should be higher than the low turnover portfolios beta. And because the low turnover portfolios responds to the market portfolio are more sluggish, the low turnover portfolio returns should respond better to the lagged market returns. Because I've constructed portfolios that are short in the low turnover portfolios, my lagged betas should be negative.

Same applies for the lead betas. Because the market portfolio is equal-weighted and constructed of all the stocks that are part of the sample, it should be somewhere in the middle ground in adjustment speed. If the lead betas are positive that would mean that the market portfolio is running behind of the high turnover portfolios, which is the hypothesis and expectation here.

Table 5.

Size = size quartile, LHS = Left hand side of the equation (returns). $\sum^{-2}_{k=-1} b_{O,k}$ is the sum of the lead betas, $b_{O,0}$ is the contemporaneous beta and $\sum^{5}_{k=1} b_{O,k}$ is the sum of the lagged betas and $\bar{R}^2$ is the adjusted coefficient of determination. ***, **, * refer to significance at 1, 5 and 10 percent levels, respectively.

| Daily returns | | | | | |
|---|---|---|---|---|---|
| Size | LHS | $\sum^{-5}_{k=-1} b_{O,k}$ | $b_{O,0}$ | $\sum^{5}_{k=1} b_{O,k}$ | $\bar{R}^2$ |
| 1 | P14 – P11 | -0.0465** | 0.5632*** | -0.0808** | 0.22 |
| 2 | P24 – P21 | 0.0735** | 0.5606*** | -0.0670** | 0.44 |
| 3 | P34 – P31 | 0.1252*** | 0.5597*** | -0.1362*** | 0.48 |
| 4 | P44 − P41 | -0.1132*** | 0.4991*** | 0.0717** | 0.46 |

| Weekly returns | | | | | |
|---|---|---|---|---|---|
| Size | LHS | $\sum^{2}_{k=-1} b_{O,k}$ | $b_{O,0}$ | $\sum^{2}_{k=1} b_{O,k}$ | $\bar{R}^2$ |
| 1 | P14 – P11 | -0.0142 | 0.6491*** | -0.1040** | 0.39 |
| 2 | P24 – P21 | 0.0264 | 0.6403*** | -0.0899** | 0.56 |
| 3 | P34 – P31 | 0.0377* | 0.5848*** | -0.1174*** | 0.55 |
| 4 | P44 − P41 | 0.0197 | 0.5059*** | -0.0885** | 0.49 |

### *3.4.1 Daily returns*

In daily returns every value is significant either at 5 percent or 1 percent level. The contemporaneous betas are all very clearly positive, but the sum of lagged betas is negative only in the first three size quartiles, meaning that, like in the VAR regressions, the lead-lag effects seem to disappear in the largest quartile. In addition, sum of the lead betas in the largest (and smallest) size quartile is negative.

So with 5 betas taken in to account the size factor seems to be more dominant, because the portfolio with the larger firms inside each size quartile is the one that seems to either lead the market returns (Sizes 1 and 4) or at least adjust faster (Sizes 2 and 3).

Comparing the Dimson beta regression daily results to those of the replication sample (Appendix 3), the historical evolvement is the clearest out of all statistics looked at in this study. The contemporaneous betas have smoothened out between size quartiles, and the lead and especially lagged betas have moved towards zero.

*3. 4. 2 Weekly returns*

Interestingly in weekly returns all the sums of lagged betas are negative and contemporaneous betas positive, all at the 1 percent or 5 percent level, despite a deviation in the daily returns.

So contrary to the cross-autocorrelations and VAR regressions, the Dimson beta regression results are more convincing when using weekly returns than daily returns. The lead betas are positive in sizes 2, 3 and 4. And even in size 1 the estimate is less negative (-0.0142 weekly returns vs -0.0465 daily returns) when using weekly returns. The $\bar{R}^2$:s are also bigger with weekly returns.

Comparing the weekly returns against the replication shows similar evolution. The contemporaneous betas have smoothened out between size quartiles and lead and lag betas have moved towards zero, however the changes and trend in values is not as drastic as it is with daily returns.

## 4. Conclusions & Discussion of Further Research

Based on VAR and Dimson beta regressions, turnover as a stand-in for trading volume has held independent value as a determinant of cross-autocorrelation patterns in NYSE & AMEX stock returns between 1963 and 2019. Although there are a couple of estimates in the regressions that do not support the hypothesis, scrutinizing the results of the main sample separately from replication results or the original study by Swaminathan and Chordia (2000) indicates that trading volume has played a role in the lead-lag patterns observed in stock returns, supported by mostly significant results in the regressions and Z-tests.

Even though there are estimates contrary to this conclusion, one has to judge these results in light of the long lasting previous research evidence about sizes impact on cross-autocorrelations. The biggest counter-evidence towards hypothesis comes from the size quartile 4, where the high turnover portfolios average firm is about one fourth in size of the average firm in the low turnover portfolio. Despite this, even that quartile provides significant results supporting hypothesis in some of the regressions. Strongest evidence comes from size quartile 3, which has exclusively significant results, even though the high and low turnover portfolios average firm size is very similar.

With that I also have to acknowledge the size factors strong impact to these patterns, even though that was not the point of this study, the regressions still manage to provide some evidence to the size factors benefit.

Now including the replication sample (1963-1997) to discussion, it is clear that trading volumes value as a determinant of cross-autocorrelations has diminished over time. Reason might be because of, like mentioned earlier, finance research has a tendency to destroy return predictability (McLean & Pontiff, 2016). Another reason might be that the more traditional market barriers have lowered over time and the market has become more efficient. Former research of transaction costs etc. affecting autocorrelations were discussed in the literature review, but my results offers a chance to revisit some of the earlier research regarding the reasoning behind the cross-autocorrelations, to see whether there have been developments to those theories.

## Appendix 1.

Replication sample cross-autocorrelations (explanations in the main sample tables):

| Panel A: Daily returns | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| $r_{ij,\,t}$ | $r_{11,\,t}$ | $r_{14,\,t}$ | $r_{21,\,t}$ | $r_{24,\,t}$ | $r_{31,\,t}$ | $r_{34,\,t}$ | $r_{41,\,t}$ | $r_{44,\,t}$ |
| $r_{11,\,t-1}$ | 0.20 | 0.23 | 0.28 | 0.14 | 0.25 | 0.10 | 0.12 | 0.06 |
| $r_{14,\,t-1}$ | 0.35 | 0.31 | 0.39 | 0.21 | 0.35 | 0.14 | 0.17 | 0.09 |
| $r_{21,\,t-1}$ | 0.32 | 0.28 | 0.37 | 0.18 | 0.34 | 0.12 | 0.16 | 0.07 |
| $r_{24,\,t-1}$ | 0.33 | 0.36 | 0.44 | 0.26 | 0.41 | 0.19 | 0.22 | 0.13 |
| $r_{31,\,t-1}$ | 0.30 | 0.28 | 0.39 | 0.19 | 0.37 | 0.14 | 0.19 | 0.09 |
| $r_{34,\,t-1}$ | 0.33 | 0.37 | 0.45 | 0.29 | 0.44 | 0.22 | 0.25 | 0.16 |
| $r_{41,\,t-1}$ | 0.27 | 0.28 | 0.39 | 0.22 | 0.42 | 0.18 | 0.25 | 0.13 |
| $r_{44,\,t-1}$ | 0.31 | 0.36 | 0.45 | 0.30 | 0.46 | 0.25 | 0.29 | 0.19 |

| Panel B: Weekly returns | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| $PF_{ij,t}$ | $r_{11,\,t}$ | $r_{14,\,t}$ | $r_{21,\,t}$ | $r_{24,\,t}$ | $r_{31,\,t}$ | $r_{34,\,t}$ | $r_{41,\,t}$ | $r_{44,\,t}$ |
| $r_{11,\,t-1}$ | 0.38 | 0.26 | 0.28 | 0.16 | 0.20 | 0.11 | 0.06 | 0.05 |
| $r_{14,\,t-1}$ | 0.42 | 0.30 | 0.32 | 0.20 | 0.24 | 0.12 | 0.08 | 0.06 |
| $r_{21,\,t-1}$ | 0.41 | 0.29 | 0.33 | 0.19 | 0.27 | 0.13 | 0.10 | 0.07 |
| $r_{24,\,t-1}$ | 0.39 | 0.32 | 0.35 | 0.22 | 0.28 | 0.15 | 0.11 | 0.08 |
| $r_{31,\,t-1}$ | 0.37 | 0.27 | 0.33 | 0.19 | 0.28 | 0.13 | 0.11 | 0.07 |
| $r_{34,\,t-1}$ | 0.37 | 0.32 | 0.36 | 0.24 | 0.30 | 0.16 | 0.14 | 0.10 |
| $r_{41,\,t-1}$ | 0.30 | 0.23 | 0.30 | 0.17 | 0.27 | 0.12 | 0.13 | 0.07 |
| $r_{44,\,t-1}$ | 0.34 | 0.29 | 0.33 | 0.23 | 0.29 | 0.16 | 0.14 | 0.10 |

## Appendix 2.

Replication sample VAR regressions (explanations in the main sample tables):

| Panel A: Daily returns | | | | | | |
|---|---|---|---|---|---|---|
| LHS | L1 | Low | H1 | High | $R^2$ | Z(A) |
| P11 | -0.0435* | 0.1131*** | 0.3096*** | 0.4708*** | 0.16 | 6.78*** |
| P14 | 0.0703*** | 0.1517*** | 0.2509*** | 0.3325*** | 0.11 | |
| P21 | -0.0054 | 0.2187*** | 0.2294*** | 0.2340*** | 0.22 | 6.13*** |
| P24 | -0.1469*** | -0.0695 | 0.3154*** | 0.3909*** | 0.08 | |
| P31 | 0.0385 | 0.1720*** | 0.1862*** | 0.2061*** | 0.21 | 4.44*** |
| P34 | -0.2410*** | -0.3087** | 0.3052*** | 0.4471*** | 0.06 | |
| P41 | 0.0382 | 0.0407 | 0.1556*** | 0.1774*** | 0.09 | 3.27*** |
| P44 | -0.1818** | -0.3164*** | 0.2874*** | 0.4034*** | 0.05 | |

| Panel B: Weekly returns | | | | | | |
|---|---|---|---|---|---|---|
| P11 | 0.1256*** | | 0.2409*** | | 0.18 | 1.73** |
| P14 | 0.0661 | | 0.2578*** | | 0.09 | |
| P21 | 0.1220*** | | 0.1323*** | | 0.12 | 0.82 |
| P24 | -0.0098 | | 0.2266*** | | 0.05 | |
| P31 | 0.0602 | | 0.1308*** | | 0.09 | 1.31* |
| P34 | -0.0852 | | 0.2001*** | | 0.03 | |
| P41 | 0.0412 | | 0.0614** | | 0.02 | 1.17 |
| P44 | -0.0935 | | 0.1457*** | | 0.01 | |

## Appendix 3.

Replication sample Dimson beta regressions (explanations in the main sample tables):

| Daily returns | | | | | |
|---|---|---|---|---|---|
| Size | LHS | $\sum^{-2}_{k=-1} b_{O,k}$ | $b_{O,0}$ | $\sum^{5}_{k=1} b_{O,k}$ | $R^2$ |
| 1 | P14 – P11 | -0.0279 | 0.4826*** | -0.2571*** | 0.13 |
| 2 | P24 – P21 | 0.0413** | 0.7900*** | -0.3567*** | 0.60 |
| 3 | P34 – P31 | 0.1121*** | 0.8566*** | -0.4204*** | 0.65 |
| 4 | P44 − P41 | 0.1199*** | 0.5603*** | -0.2667*** | 0.50 |

| Weekly returns | | | | | |
|---|---|---|---|---|---|
| 1 | P14 – P11 | 0.0109 | 0.4947*** | -0.1896*** | 0.33 |
| 2 | P24 – P21 | 0.0240 | 0.6646*** | -0.1788** | 0.61 |
| 3 | P34 – P31 | 0.0378* | 0.6735*** | -0.1986*** | 0.59 |
| 4 | P44 − P41 | 0.0330* | 0.4801*** | -0.1218** | 0.46 |

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